Open

Invited Editorial

Tactical asset allocation for US pension investors: How tactical should the plan be?

Received (in revised form): 2nd June 2015

David Louton
is a professor of finance at Bryant University, where he teaches courses in investments and corporate finance. He holds a PhD from Michigan State University. His research interests are in portfolio management, mutual funds and options markets.

Joseph McCarthy
is a professor of finance at Bryant University, where he teaches courses in financial forecasting, derivative securities and corporate finance. He holds a doctorate in business administration from the University of Colorado. His primary research interests are in fixed income portfolio management and forecasting macroeconomic and financial time series.

Stephen Rush
has worked as a securities analyst and is currently a PhD candidate at the University of Connecticut. He holds a CFA charter as well as MBA and MSF degrees from Boston College. His primary research interests are in market microstructure.

Hakan Saraoglu
is a professor of finance at Bryant University, where he teaches international financial management, international investments and corporate finance. He holds a PhD from Michigan State University. His research interests are in portfolio management, mutual funds, options markets, international finance and financial modeling.

Ognjen Sosa
is a team leader and portfolio manager of Global Institutional Solutions in the Global Asset Allocation Group at Fidelity investments. He is a CAIA and FRM charter holder and holds MEng, MS and MBA degrees from the University of Florida.

Correspondence: David Louton, Department of Finance, Bryant University, 1150 Douglas Turnpike, Smithfield, Rhode Island 02917-1284, USA

ABSTRACT Following the recession in the early 2000s, US corporate and public defined benefit (DB) plans faced unprecedented uncertainty with respect to their funding requirements going forward. Just as capital market performance started helping plan sponsors improve the health of their DB plans, the financial crisis of 2007–2009 delivered another serious blow. Consequently, plan sponsors turned their focus on improving their risk management practices and determining whether asset managers with proven track records should be given more broadly defined mandates, specifically designed to allow for more effective navigation in more volatile markets. Tactical asset allocation (TAA) strategies seek to add value by deviating from a plan's policy mix based on the manager's view on the attractiveness of various asset classes, regions and sectors within the investment opportunity set. Although TAA can add value to a portfolio, manager skill and risk taking are required to achieve reasonable risk-adjusted performance. The timing and magnitude of shifts from the policy mix can have a significant impact on the portfolio outcomes. Therefore, it is essential for investors to assess the appropriate role of TAA in their portfolio management process and evaluate the risk-return tradeoff of tactical deviations from policy. Our study uses a sample of historical returns from the global financial markets and simulation methodology to investigate the relationship of tactical band size and rebalancing practices to various measures of portfolio performance. The results show that providing investment managers with limited flexibility in making asset allocation decisions may allow DB plans to weather down markets better. For DB plan sponsors who are considering giving managers less constrained mandates, manager skill in adding value through TAA decisions should be considered.

Journal of Asset Management (2015) **16,** 427–436. doi:10.1057/jam.2015.26;
published online 3 September 2015

Keywords: tactical; asset; allocation; defined; benefit; pension

The online version of this article is available Open Access

The asset allocation decision is an important component of the portfolio management process. Institutional and individual investors must ensure that their portfolio composition is in line with their risk-return objectives by selecting appropriate weights for the asset classes in their portfolio. As it is important to maintain the policy weights of a portfolio commensurate with the investor's long-term strategic asset allocation objectives, it may also be beneficial to allow tactical shifts based on current and expected market conditions. The recent financial crisis motivated US corporate and public defined benefit (DB) plans to reconsider their approach to investment management, especially in the area of asset allocation. The following quotes from respondents to the *2010 Pyramis US Defined Benefit Survey* illustrate the perspectives of plan sponsors importance on tactical asset allocation (TAA).

> Portfolios that had tactical or opportunistic allocations were able to take advantage of opportunities in the midst of the financial crisis. This is something to consider going forward.(*Investment Analyst, Municipal Employee Retirement System*)

> We'll create higher bands on our asset allocation so it's more flexible and so that if the market rebounds, we won't have to rebalance quite as quickly.(*Portfolio Manager/Investment Manager, County Pension System*)

Additionally, the timely execution of asset allocation changes was identified as the top priority of public DB plans. Twenty-eight per cent of public DB plans ranked it as number one versus only 11 per cent of corporate plans (2010 Pyramis US Defined Benefit Survey, 2010). Historically, pension investors have had access to standalone TAA strategies managed around a pre-specified strategic asset mix with bands that vary from +/−5 per cent to completely unconstrained. More recently, a new trend has emerged with asset managers and investment consulting firms focusing on customized solutions and typically packaging these offerings branded as 'CIO Outsourcing' or 'Total Portfolio Management'. As part of these broader mandates, managers are offering TAA and/or tail-risk hedging overlays. The objective of this study is to help inform plan sponsors on the amount of discretion they should consider giving to a manager should they choose to implement an overlay program. To the extent that proper scaling is applied, results of this study can be easily ported to plan sponsors considering investing only a portion of their assets in an established TAA strategy. The timing and magnitude of shifts from a target asset allocation can have a significant impact on the portfolio outcomes. Therefore, it is essential for investors to assess the appropriate role of TAA in their portfolio management process and evaluate the risk-return tradeoff of deviations from policy weights.

There are few studies in the academic research literature that focus on TAA bands. Ammann and Zimmermann (2001) examine the relationship between various measures of tracking error, asset allocation bands of portfolios and rebalancing practices. Using actual return data covering the January 1985 to June 1998 period, they show that large TAA bands generate small tracking errors. They also find that the correlation between tactical portfolios and their benchmarks are very sensitive to the tracking accuracy of asset classes. Using a sample from the municipal bond market, Kuenzi (2004) provides a framework for measuring the relationship between tactical ranges and tracking error within a single asset class. Lewis *et al* (2007) develop a dynamic Value at Risk (VaR) TAA strategy to control the risk and expected losses of a balanced fund. They suggest that their strategy provides fund managers with prescribed tactical shifts in their asset allocation that are consistent with their level of risk aversion. Focusing on the more general question of whether TAA can work, Nam and Branch (1994) build a market timing model and suggest that TAA may add value. Ahmed *et al* (2002) assess the potential benefits of multi-style rotation strategies.

We use historical returns from the global financial markets and a set of simulation methodologies to investigate the relationship of band size and rebalancing practices to various measures of portfolio performance. The objective of this study is to help inform plan sponsors on the amount of discretion they should consider giving to a manager should they choose to implement a TAA program. With proper scaling, our findings can be easily applied to plans considering investing only a portion of their assets in an established TAA strategy. We include a discussion of our sample data, methodology, and results and conclude by explaining the implications of our study for DB plan sponsors.

DATA, METHODOLOGY AND RESULTS

The data sample in this study covers the January 1990 to December 2009 period and includes monthly returns on various asset classes including US equity, international equity, fixed income, real estate and alternative assets. We use the Russell 3000, MSCI EAFE, Barclays Capital US Aggregate Bond, FTSE NAREIT Equity Only and HFRI Fund Weighted Composite Index as proxies for US equity, international equity, fixed income, real estate and alternative assets, respectively. Table 1 shows the summary statistics of the asset class returns during the sample period and Table 2 shows the asset allocation weights used by the typical US DB plan.

We investigate the risk-return trade-offs implicit in the tactical band size decision by using the stationary bootstrap methodology proposed by Politis and Romano (1994). The stationary bootstrap procedure involves resampling a time series in data blocks of random length, where the block length follows a geometric distribution. The resulting resampled time series is stationary and the serial correlation structure of the observations within each block of the original time series is preserved. The stationary bootstrap procedure has been used in a variety of studies in finance (see for example Norsworthy *et al*, 2001; Balcombe and Tiffin, 2002; Koopman *et al*, 2005; Boyson, 2008; Ledoit and Wolf, 2008; Cao, 2009; James and Yang, 2010; and Nomikos and Pouliasis, 2011).

In our base case, we use the typical allocation of a US DB plan (2008 Pyramis Defined Benefit Research Round, 2008) as the starting strategic asset mix (that is, policy mix) consisting of 45 per cent US equity, 16 per cent non-US equity, 28 per cent fixed income, 5 per cent real estate and 6 per cent alternatives/other. Our first rule set is as follows: (i) a +/−5 per cent bandwidth for each asset class is established, (ii) when any asset class exceeds its band, the entire portfolio is rebalanced to policy weights, (iii) allocations are monitored on a monthly basis but a rebalancing is only implemented during a month when asset weights move outside the established bandwidth. Using the stationary bootstrap

Table 1: Summary statistics of the proxies for asset classes in the US defined benefit plan portfolios

			Correlation coefficient				
	Average monthly return (%)	*Standard deviation of monthly returns (%)*	*US equity*	*Non-US equity*	*Fixed income*	*Real estate*	*Alternatives/other*
US equity	0.77	4.40	1.00	0.73	0.17	0.56	0.77
Non-US equity	0.30	5.03		1.00	0.14	0.46	0.65
Fixed income	0.57	1.12			1.00	0.18	0.11
Real estate	0.95	5.64				1.00	0.42
Alternatives/other	0.98	2.05					1.00
Equally weighted benchmark	0.72	2.90					
Benchmark for the US defined benefit plans (all)	0.66	2.96					

Table 2: Asset allocations of the US defined benefit plans

	All	*Corporate*	*Public*	*Large*	*Mid*
US equity	45	46	43	43	46
Non-US equity	16	15	17	17	15
Fixed income	28	29	27	28	29
Real estate	5	4	7	5	5
Alternatives/other	6	6	6	7	5
Total	100	100	100	100	100

Source: 2008 Pyramis Defined Benefit Research Round.

methodology proposed by Politis and Romano (1994), we generate monthly return series for each asset class resampled from our sample data covering the January 1990 to December 2009 period. Then, we apply our rule set to the portfolio of asset classes using the resampled return series for each asset class.

For each resulting portfolio, we calculate the arithmetic average return, standard deviation of the returns, correlation of the returns with the benchmark portfolio returns, information ratio and two different measures of tracking error. We define the information ratio as follows:

$$IR_i = \frac{(1/T)\sum_t \left(r_{i,t} - r_{B,t}\right)}{s_{r_{i,t}-r_{B,t}}} \qquad (1)$$

where $r_{i,t}$ is return for portfolio i in month t, $r_{B,t}$ is return for the benchmark portfolio in month t, $s_{r_{i,t}-r_{B,t}}$ is the standard deviation of the differences in portfolio i returns and benchmark portfolio returns, and T is the number of months in the sample period.

We calculate $TE1$ and $TE2$ using the following equations:

$$TE1_i = \sqrt{\frac{1}{T-1}\sum_t \left(r_{i,t} - r_{B,t}\right)^2} \qquad (2)$$

$$TE2_i = s_{r_i}\sqrt{1-\rho_{iB}^2} \qquad (3)$$

where s_{r_i} is the standard deviation of returns for portfolio i and ρ_{iB} is the correlation of returns of portfolio i and the benchmark portfolio.

We repeat this procedure by generating a set of 5000 resampled return series for each band size between 1 and 5 per cent enabling us to calculate distributions for each portfolio metric. The benchmark used for performance analysis is the portfolio rebalanced to policy weights in every period.

Table 3 shows the summary statistics of selected portfolio metrics across simulation runs. Correlation of the portfolio with the benchmark is very high for band sizes of 1–5 per cent. The mean value of the portfolio correlation is 99.9 per cent for each band size as shown in Panel B of Table 3. Similarly, these portfolios generate very low tracking error within the band size range of 1–5 per cent, as shown in Table 3. The value of the information ratio of the portfolio

Table 3: Summary statistics of portfolio outcomes across simulation runs

Panel A. Mean information ratio and tracking error of portfolio outcomes across simulation runs

Band size (%)	*1*	*2*	*3*	*4*	*5*
Information ratio	0.05	0.42	0.30	0.31	0.36
Tracking error	0.03%	0.05%	0.08%	0.10%	0.13%

Panel B. Summary statistics

	Mean	*Median*	*Min*	*Max*	*StDev*
			1% band size		
Correlation	0.999974	0.999974	0.999943	0.999987	0.000004
Information ratio	0.05	0.05	−0.42	0.64	0.19
Tracking error	0.03%	0.03%	0.02%	0.03%	0.01%
			2% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999873	0.999875	0.999786	0.999931	0.000021
Information ratio	0.42	0.42	−0.22	0.94	0.21
Tracking error	0.05%	0.05%	0.04%	0.07%	0.01%
			3% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999690	0.999698	0.999497	0.999817	0.000052
Information ratio	0.30	0.30	−0.31	0.78	0.19
Tracking error	0.08%	0.08%	0.06%	0.11%	0.01%
			4% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999453	0.999457	0.999116	0.999702	0.000096
Information ratio	0.31	0.31	−0.39	0.83	0.20
Tracking error	0.10%	0.10%	0.07%	0.14%	0.02%
			5% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999136	0.999150	0.998523	0.999525	0.000162
Information ratio	0.36	0.36	−0.25	0.92	0.20
Tracking error	0.13%	0.13%	0.09%	0.19%	0.02%

ranges between −0.41 and 0.93 across the simulation runs.

Figure 1 illustrates an interesting finding. As the band size increases from 1 to 5 per cent, the mean information ratio across simulation runs increases and peaks at around 0.45 at the 2 per cent band size before declining to around 0.35 at the 5 per cent band size. Figure 2 shows that the mean value of the tracking error across simulation runs increases from around 26 basis points (bps) at the 1 per cent band size to around 13 bps at the 5 per cent band size. When DB plan sponsors experiment with delegating greater authority to their managers to shift among asset classes, it may

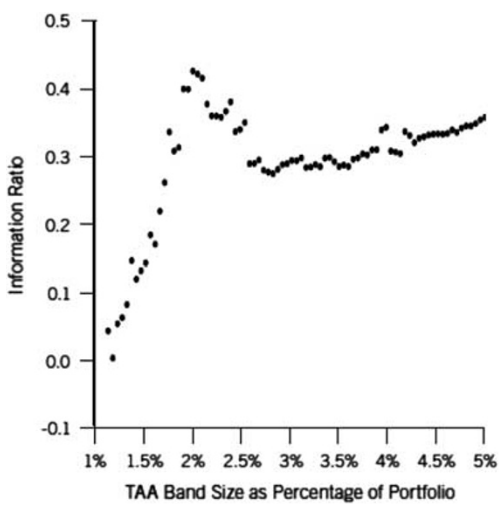

Figure 1: Average information ratio across simulation runs for varying band sizes.

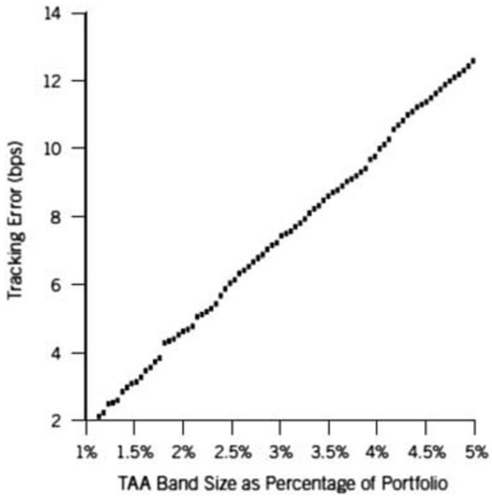

Figure 2: Average tracking error across simulation runs for varying band sizes.

make sense to start with a 2 per cent band. The strength of the information ratio at the 2 per cent level should be attractive to plan sponsors who tend to allow small adjustments, rather than big shifts, in asset class allocations. Providing investment managers with this limited flexibility in asset allocation may seem conservative, but may still allow DB plans the potential to weather down markets better. For plan sponsors who are considering larger shifts, the simulation suggests they should be cautious. The average increase in returns may be offset by greater risk above the 2 per cent band size.

As some plan sponsors may provide their managers with additional flexibility to deviate

Table 4: Summary statistics of portfolio outcomes across simulation runs (perfect foresight)

Panel A. Mean information ratio and tracking error of portfolio outcomes across simulation runs

Band size (%)	*1*	*2*	*3*	*4*	*5*
Information ratio	3.15	3.41	3.66	4.07	4.26
Tracking error	0.08%	0.16%	0.24%	0.32%	0.38%

Panel B. Summary statistics

	Mean	*Median*	*Min*	*Max*	*StDev*
			1% band size		
Correlation	0.999907	0.999908	0.999844	0.999943	0.000017
Information ratio	3.15	3.14	2.87	3.36	0.10
Tracking error	0.08%	0.08%	0.06%	0.11%	0.01%
			2% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999625	0.999627	0.999375	0.999768	0.000068
Information ratio	3.41	3.40	3.09	3.63	0.10
Tracking error	0.16%	0.16%	0.13%	0.22%	0.02%
			3% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999130	0.999134	0.998579	0.999464	0.000154
Information ratio	3.66	3.67	3.33	3.92	0.11
Tracking error	0.24%	0.24%	0.19%	0.32%	0.03%
			4% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.998588	0.998589	0.997751	0.999080	0.000245
Information ratio	3.15	3.14	2.87	3.36	0.10
Tracking error	0.08%	0.08%	0.06%	0.11%	0.01%
			5% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.997651	0.997674	0.996274	0.998426	0.000385
Information ratio	4.26	4.27	3.79	4.59	0.12
Tracking error	0.39%	0.38%	0.30%	0.51%	0.04%

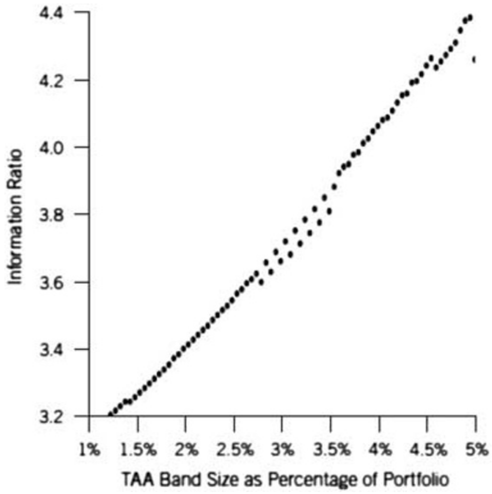

Figure 3: Average information ratio across simulation runs for varying band sizes (perfect foresight).

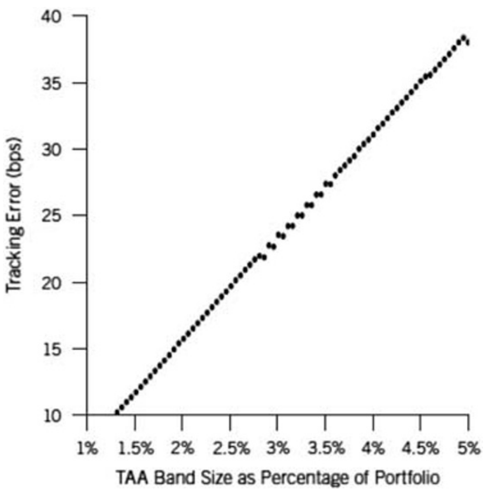

Figure 4: Average tracking error across simulation runs for varying band sizes (perfect foresight).

from their policy weights based on their skill level, it is important to investigate the impact of manager's skill on a plan's portfolio performance. We use a perfect foresight assumption and the following rule set to calculate performance metrics across simulation runs: (i) a +/−5 per cent bandwidth for each asset class is established, (ii) each month the asset classes are ranked by next month's return, (iii) the best performing asset class is over-weighted by underweighting the worst performing asset class, (iv) the trade amount is the maximum weight that can be traded between the best and worst asset class without exceeding either bandwidth.

Table 4 presents the summary statistics of selected portfolio metrics across simulation runs under the perfect foresight assumption. It shows that tracking error is very low within the band size range of 1–5 per cent.
As expected, the mean of the information ratio increases as the band size increases. Figure 3 shows that as the band size increases from 1 to 5 per cent, the mean information ratio across simulation runs increases from around 3.2 at the 1 per cent band size to around 4.3 at the 5 per cent band size. Figure 4 indicates that, under the perfect foresight assumption, the mean value of the tracking error across simulation runs increases from around 8 bps at the 1 per cent band size to around 38 bps at the 5 per cent band size.

Portfolio managers may demonstrate their skill through successful uses of strategies such as momentum investing. To examine portfolio performance for a manager using a momentum strategy we use the following rule set: (i) a +/−5 per cent bandwidth for each asset class is established, (ii) the previous 36 months are used to calculate the total return from each asset class, (iii) each month the two asset classes with the highest return receive the maximum weight while the two asset classes with the lowest return receive the minimum weight, (iv) the remaining asset class receives a neutral weight.

Table 5, which includes the selected portfolio metrics across simulation runs for a momentum scenario, shows that the portfolio has high correlation with its benchmark and its tracking error is low within the band size range of 1-5 per cent. The mean information ratio for the simulated portfolios is positive and shows slightly increasing values across the band size spectrum. Figure 5 demonstrates this graphically. Figure 6 indicates that the mean value of the tracking error across simulated

Table 5: Summary statistics of portfolio outcomes across simulation runs (momentum)

Panel A. Mean information ratio and tracking error of portfolio outcomes across simulation runs

Band size (%)	*1*	*2*	*3*	*4*	*5*
Information ratio	0.33	0.33	0.34	0.34	0.34
Tracking error	0.08%	0.15%	0.23%	0.29%	0.36%

Panel B. Summary Statistics

			1% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.999749	0.999751	0.999609	0.999856	0.000044
Information ratio	0.33	0.30	−0.44	1.04	0.27
Tracking error	0.08%	0.07%	0.05%	0.12%	0.02%
			2% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.998989	0.998998	0.998411	0.999431	0.000179
Information ratio	0.33	0.30	−0.44	1.06	0.27
Tracking error	0.15%	0.14%	0.10%	0.23%	0.03%
			3% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.997705	0.997718	0.996376	0.998739	0.000406
Information ratio	0.34	0.30	−0.43	1.07	0.28
Tracking error	0.23%	0.21%	0.14%	0.35%	0.04%
			4% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.995889	0.995923	0.993478	0.997791	0.000732
Information ratio	0.34	0.31	−0.43	1.09	0.28
Tracking error	0.29%	0.28%	0.19%	0.46%	0.06%
			5% band size		
	Mean	*Median*	*Min*	*Max*	*StDev*
Correlation	0.993529	0.993590	0.989695	0.996599	0.001162
Information ratio	0.34	0.31	−0.43	1.11	0.28
Tracking error	0.36%	0.35%	0.23%	0.57%	0.07%

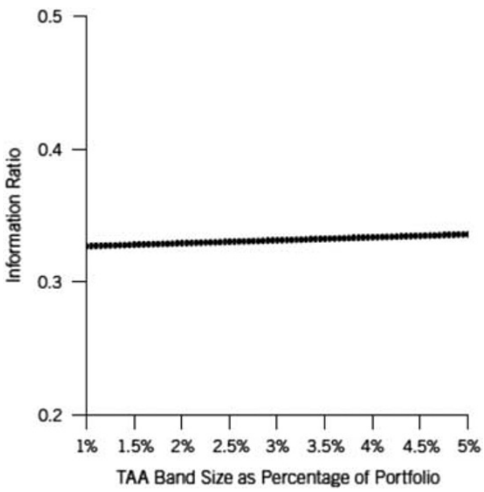

Figure 5: Average information ratio across simulation runs for varying band sizes (momentum).

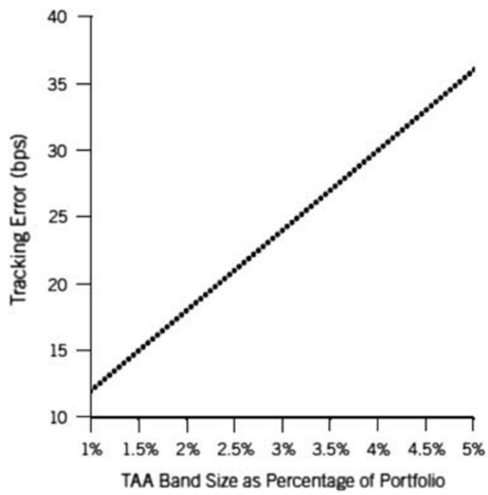

Figure 6: Average tracking error across simulation runs for varying band sizes (momentum).

momentum portfolios increases from around 7 bps at the 1 per cent band size to around 35 bps at the 5 per cent band size.

CONCLUSIONS

In this study we use simulation analysis to compute risk and performance metrics of a portfolio resembling the allocation of a typical US DB pension plan rebalanced monthly based on a simple rebalancing rule and with tactical band sizes varying from 1 to 5 per cent. Our results show that such a portfolio is highly correlated with the benchmark portfolio that is rebalanced to the policy weights each month. Two proxies for tracking error also show that the portfolio tracks the benchmark very closely. The mean of the portfolio's information ratio across simulation runs achieves a peak value of 1.2 at the 2 per cent band size and declines to around 0.35 as the band size increases to 5 per cent. This finding has implications for DB plan sponsors when they decide how much authority to give their managers to shift among asset classes. Those DB sponsors that tend to allow small adjustments in asset class allocations may choose to start with a 2 per cent band. As the average increase in returns may be offset by greater risk above the 2 per cent band size, the simulation results suggest the DB plan sponsors considering larger shifts should be cautious.

Incorporating the impact of manager's skill into our simulation analysis using a perfect foresight assumption shows that plan sponsors can increase portfolio performance by allowing a higher tactical band size. However, before plan sponsors allow bigger shifts, they should feel confident in the skill of the person or organization determining the changes to a portfolio's asset allocation. Also, our simulation runs based on the momentum rule show that the mean of the portfolio's information ratio is positive but exhibits only slight increases across the band size spectrum. Plan sponsors must have confidence in the effectiveness of a given portfolio rebalancing strategy before allowing a manager to use larger TAA band sizes.

REFERENCES

Ahmed, P., Lockwood, L.J. and Nanda, S. (2002) Multistyle rotation strategies. *Journal of Portfolio Management* 28(3): 17–29.

Ammann, M. and Zimmermann, H. (2001) Tracking error and tactical asset allocation. *Financial Analysts Journal* 57(2): 32–43.

Balcombe, K. and Tiffin, R. (2002) Bootstrap testing of the expectations hypothesis with the term structure of interest rates. *Applied Economics Letters* 9(9): 563–566.

Boyson, N.M. (2008) Hedge fund performance persistence: A new approach. *Financial Analysts Journal* 64(6): 27–44.

Cao, B. (2009) Testing Generic Rebalancing Policies for Retirement Portfolios. Working Paper.

James, J. and Yang, L. (2010) Stop-losses, maximum drawdown-at-risk and replicating financial time series with the stationary bootstrap. *Quantitative Finance* 10(1): 1–12.

Koopman, S., Jungbacker, J.B. and Hol, E. (2005) Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance* 12(3): 445–475.

Kuenzi, D.E. (2004) Tracking error and the setting of tactical ranges. *The Journal of Investing* 13(1): 35–44.

Nam, J. and Branch, B. (1994) Tactical asset allocation: Can it work? *The Journal of Financial Research* 17(4): 465–479.

Ledoit, O. and Wolf, M. (2008) Robust performance hypothesis testing with the sharpe ratio. *Journal of Empirical Finance* 15(5): 850–859.

Lewis, N., Okunev, J. and White, D. (2007) Using a value at risk approach to enhance tactical asset allocation. *The Journal of Investing* 16(4): 100–107.

Nomikos, N.K. and Pouliasis, P.K. (2011) Forecasting petroleum futures markets volatility: The role of regimes and market conditions. *Energy Economics* 33(2): 321–337.

Norsworthy, J.R., Demirel, O. and Gorener, R. (2001) Change management and the new industrial revolution. *Proceedings of IEMC 2001*, doi: 10.1109/IEMC.2001.960580.

Politis, D.N. and Romano, J.P. (1994) The stationary bootstrap. *Journal of the American Statistical Association* 89(428): 1303–1313.

Pyramis Global Advisors (2008) Pyramis Defined Benefit Research Round. internal report.

Pyramis Global Advisors (2010) Pyramis U.S. Defined Benefit Survey. internal report.

This work is licensed under a Creative Commons Attribution

3.0 Unported License. The images or other third party material in this article are included in the article's Creative Commons license, unless indicated otherwise in the credit line; if the material is not included under the Creative Commons license, users will need to obtain permission from the license holder to reproduce the material. To view a copy of this license, visit http://creativecommons.org/licenses/by/3.0/